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Influence of soil spatial variability and stochastic Ground-Motion on the dynamic behavior of a slope

Tamara Al-Bittar¹, Dalia Youssef Abdel Massih², Abdul Hamid Soubra³ M.ASCE,
Fadi Hage Chehade⁴

¹ PhD student, University of Nantes, GeM, UMR CNRS 6183, Bd. de l'université, BP 152, 44603 Saint-Nazaire cedex, France; E-mail: Tamara.Al-Bittar@univ-nantes.fr.

² Assistant Professor, Notre Dame University, Louaize, Civil and Environmental Engineering, P.O. Box: 72 Zouk Mikael, Lebanon; E-mail: dabdelmassih@ndu.edu.lb.

³ Professor, University of Nantes, GeM, UMR CNRS 6183, Bd. de l'université, BP 152, 44603 Saint-Nazaire cedex, France; E-mail: Abed.Soubra@univ-nantes.fr.

⁴ Professor, Modeling Center, PRASE, Doctoral School of Science and Technology, Beirut, Lebanese University, Lebanon; E-mail: fchehade@ul.edu.lb.

ABSTRACT

A probabilistic dynamic approach is used for the slope stability analysis. In this approach, the effect of both the soil spatial and the Ground-Motion (GM) time variabilities on the dynamic responses are studied and discussed. The soil shear modulus G is considered as an isotropic non-Gaussian random field. The simulation of variable acceleration time histories based on a real target accelerogram is done using a fully nonstationary stochastic model (i.e. which has nonstationary characteristics in both time and frequency domains). The deterministic model is based on numerical simulations using the dynamic option of the finite difference code FLAC^{3D}. An efficient uncertainty propagation methodology which builds up a sparse polynomial chaos expansion for the dynamic responses is used. The probabilistic numerical results have shown that: (i) the decrease in the autocorrelation distance of G (i.e. the soil heterogeneity) leads to a small variability of the dynamic responses; (ii) adding the randomness of the earthquake GM has a significant influence on the variability of the dynamic responses; (iii) the probabilistic mean values of the dynamic responses are more critical than the deterministic ones.

INTRODUCTION

The seismic stability of slopes is widely investigated in literature using deterministic approaches. However, the material properties of soils are known to vary greatly from point to another, and many of these older pen and paper methods have difficulty to successfully model this heterogeneity. Things are more complicated when dealing with dynamic loading situations. In this paper, the effect of both the soil spatial variability and the time variability of Ground-Motion (GM) on the dynamic responses of a simple slope are studied. Few authors have worked on the analysis of the dynamic horizontal soil behavior using probabilistic approaches where the spatial variability of soil properties and the time variability of seismic excitations were considered [Koutsourelakis et al (2002), Popescu et al (2006), ...]. In these works, three main deficiencies can be detected: First, the classical Monte Carlo Simulation (MCS) methodology with a small number of realizations is used to determine the

probability density function (PDF) of the system responses (e.g. 50 simulations). It is well known that in order to be a rigorous approach, MCS is very time-expensive. Second, the stochastic model for generating synthetic acceleration time-histories is based on the spectral representation in order to simulate accelerograms which are compatible with a prescribed response spectrum and not real GM acceleration. Finally, the spatial variability of soil properties is studied for specific autocorrelation distances.

In this study, the three mentioned deficiencies will be improved by (i) using a more efficient probabilistic approach instead of the crude MCS which is the Sparse Polynomial Chaos Expansion (SPCE) [Blatman and Sudret (2010), Al-Bittar and Soubra (2011)]; (ii) simulating the stochastic accelerogram using the method given by Rezaeian and Der Kiureghian (2010). This method has the advantage of solving the majority of problems encountered in the previous models [Rezaeian and Der Kiureghian (2008)]; (iii) considering a large range of autocorrelation distances for the soil shear modulus G modeled as an isotropic non-Gaussian random field. The Expansion Optimal Linear Estimation (EOLE) methodology proposed by Li and Der Kiureghian (1993) is used to generate this random field.

The deterministic model is based on numerical simulations using the dynamic option of the finite difference code FLAC^{3D}. Samples of the synthetic GM time-histories were generated and a dynamic stochastic calculation for each realization was performed to compute the dynamic responses (i.e. the permanent displacement at the toe of the slope and the maximum amplification of the acceleration at the top of the slope). The paper is organized as follows: The first three sections aim at presenting (i) the method used to generate the random field of the shear modulus G , (ii) the method used to generate the stochastic synthetic accelerograms based on a real target one and finally (iii) the SPCE methodology employed to determine the analytical expression of the dynamic system responses. These sections are followed by a presentation of the probabilistic numerical results in which only the soil spatial variability is first considered and then combined with the time variability of the GM in order to highlight its effect on the variability of the dynamic responses.

GENERATION OF NON-GAUSSIAN RANDOM FIELD

Let's consider the non-Gaussian random field $Z_G^{NG}(x, y)$ (where G represents the soil shear modulus) described by: (i) constant mean μ_G and standard deviation σ_G , (ii) non-Gaussian marginal cumulative distribution function F_G , and (iii) a square exponential autocorrelation function $\rho_z^{NG}[(x, y), (x', y')]$ which gives the values of the correlation function between two arbitrary points (x, y) and (x', y') . This autocorrelation function is given as follows:

$$\rho_z^{NG}[(x, y), (x', y')] = \exp \left(- \left(\frac{x - x'}{a_x} \right)^2 - \left(\frac{y - y'}{a_y} \right)^2 \right) \quad (1)$$

where a_x and a_y are the autocorrelation distances along x and y respectively. The EOLE method proposed by Li and Der Kiureghian (1993) is used herein to generate the random field of G . In this method, one should first define a stochastic grid

composed of q grid points (or nodes) obtained from the different combination of H points in the x (or horizontal) direction, and V points in the y (or vertical) direction assembled is a vector $Q = \{Q_n = (x_h, y_v)\}$ where $h=1, \dots, H, v=1, \dots, V$ and $n=1, \dots, q$. Notice that for the vector Q composed of q elements, the values of the field are assembled in a vector $\chi = \{\chi_n = Z(x_h, y_v)\}$ where $h=1, \dots, H, v=1, \dots, V$ and $n=1, \dots, q$. Then, one should determine the correlation matrix for which each element $\left(\Sigma_{z;z}^{NG}\right)_{i,j}$ is calculated using Equation (1) as follows:

$$\left(\Sigma_{z;z}^{NG}\right)_{i,j} = \rho_z^{NG} [Q_i, Q_j] \quad (1)$$

where $i=1, \dots, q$ and $j=1, \dots, q$. Notice that the matrix $\Sigma_{z;z}^{NG}$ in equation (2) provides the correlation between each point in the vector χ and all the other points of the same vector. The non-Gaussian autocorrelation matrix $\Sigma_{z;z}^{NG}$ should be transformed into the Gaussian space using the Nataf transformation. As a result, one obtains a Gaussian autocorrelation matrix $\Sigma_{z;z}^G$ that can be used to discretize the random field of the shear modulus G as follows:

$$\tilde{Z}_G(x, y) = \mu_G + \sigma_G \sum_{j=1}^N \frac{\xi_j}{\sqrt{\lambda_j}} \cdot \phi_j \cdot \Sigma_{z(x,y);z} \quad (3)$$

where (λ_j, ϕ_j) are the eigenvalues and eigenvectors of the Gaussian autocorrelation matrix $\Sigma_{z;z}^G$, $\Sigma_{z(x,y);z}$ is the correlation vector between each point in the vector χ and the value of the field at an arbitrary point (x, y) , ξ_j is a standard normal random variable, and N is the number of terms (expansion order) retained in EOLE method. Once the Gaussian random field is obtained, it should be transformed into the non-Gaussian space by applying the following formula:

$$\tilde{Z}_G^{NG}(x, y) = F_G^{-1} \left\{ \Phi \left[\tilde{Z}_G(x, y) \right] \right\} \quad (4)$$

where $\Phi(\cdot)$ is the standard normal cumulative density function.

It should be mentioned here that the presented method can be applied for both Gaussian and non-Gaussian random fields. Since non-negative values must be obtained for G , a non-Gaussian (lognormal) random field was used in this paper.

GENERATION OF STOCHASTIC GROUND MOTION ACCELEROGRAMS

In this paper, the method proposed by Rezaeian and Der Kiureghian (2010) was used to generate stochastic acceleration time histories from a target accelerogram. This method consists in fitting a parameterized stochastic model that is based on a modulated, filtered white-noise process to a recorded ground motion. The parameterized stochastic model in its continuous form is defined as:

$$x(t) = q(t, \alpha) \left[\frac{1}{\sigma_f(t)} \int_{-\infty}^t h[t - \tau, \lambda(\tau)] w(\tau) d\tau \right] \quad (5)$$

In this expression, $q(t, \alpha)$ is a deterministic, positive, time-modulating function with parameters α controlling its shape and intensity; $w(\tau)$ is a white-noise

process; the integral inside the curved brackets is a filtered white-noise process with $h [t - \tau, \lambda(\tau)]$ denoting the Impulse-Response Function (IRF) of the filter with time-varying parameters $\lambda(\tau)$; and $\sigma_h^2(t) = \int_{-\infty}^t h^2 [t - \tau, \lambda(\tau)] d\tau$ is variance of the integral process. Because of the normalization by $\sigma_h(t)$, the process inside the curved brackets has unit variance. As a result, $q(t, \alpha)$ equals the standard deviation of the resulting process $x(t)$. It should be clear that the modulating function $q(t, \alpha)$ completely defines the temporal characteristics of the process, whereas the form of the filter IRF and its time-varying parameters define the spectral characteristics of the process. In this study, a ‘Gamma’ modulating function is used:

$$q(t, \alpha) = \alpha_1 t^{\alpha_2 - 1} \exp(-\alpha_3 t) \quad (6)$$

where $\alpha = (\alpha_1, \alpha_2, \alpha_3)$, $\alpha_1, \alpha_3 > 0$, and $\alpha_2 > 1$. Of the three parameters, α_1 controls the intensity of the process, α_2 controls the shape of the modulating function and α_3 controls the duration of the motion. These parameters $\alpha = (\alpha_1, \alpha_2, \alpha_3)$ are related to three physically based parameters $(\bar{I}_a, D_{5-95}, t_{mid})$ which describe the real recorded GM in the time domain; where \bar{I}_a , is the Arias Intensity (AI), D_{5-95} represents the effective duration of the motion. It is defined as the time interval between the instants at which the 5 and 95% of the expected AIs are reached respectively. t_{mid} is the time at the middle of the strong-shaking phase. It is selected as the time at which 45% level of the expected AI is reached. The relations between $\alpha = (\alpha_1, \alpha_2, \alpha_3)$ and $(\bar{I}_a, D_{5-95}, t_{mid})$ are given in details in Rezaeian and Der Kiureghian (2010).

For the filter IRF, we select a form that corresponds to the pseudo-acceleration response of a single-degree-of-freedom linear oscillator:

$$h [t - \tau, \lambda(\tau)] = \begin{cases} \frac{\omega_f(\tau)}{\sqrt{1 - \zeta_f^2(\tau)}} \exp[-\zeta_f(\tau)\omega_f(\tau)(t - \tau)] \times \sin \left[\omega_f(\tau)\sqrt{1 - \zeta_f^2(\tau)}(t - \tau) \right] & t \leq \tau \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

where $\lambda(\tau) = (\omega_f(\tau), \zeta_f(\tau))$ is the set of time-varying parameters of the IRF with $\omega_f(\tau)$ denoting the frequency of the filter and $\zeta_f(\tau)$ denoting its damping ratio. These two parameters, $\omega_f(\tau)$ and $\zeta_f(\tau)$ are related to two physical parameters that describe the recorded GM in the frequency domain and which are respectively the predominant frequency and the bandwidth of the GM. For more details about the identification procedure between the recorded GM and the stochastic model described previously, the reader may refer to Rezaeian and Der Kiureghian (2008, 2010).

SPARSE POLYNOMIAL CHAOS EXPANSION (SPCE) METHODOLOGY

The polynomial chaos expansion (PCE) methodology aims at replacing a complex deterministic model whose input parameters are modeled by random variables by a meta-model which allows one to calculate the system response using an approximate analytical equation [Blatman and Sudret (2010)]. The coefficients of the PCE are computed herein using a regression approach.

For a deterministic numerical model with M input uncertain parameters, the uncertain parameters should be represented first by independent standard normal random variables $\{\xi_i\}_{i=1,\dots,M}$ gathered in a random vector ξ . The random response Γ of our mechanical model can then be expressed by a PCE of order p fixed by the user as follows:

$$\Gamma_{PCE}(\xi) = \sum_{\beta=0}^{\infty} a_{\beta} \Psi_{\beta}(\xi) \cong \sum_{\beta=0}^{P-1} a_{\beta} \Psi_{\beta}(\xi) \quad (8)$$

where P is the number of terms retained in the truncation scheme, a_{β} are the unknown PCE coefficients to be computed and Ψ_{β} are multivariate (or multidimensional) Hermite polynomials which are orthogonal with respect to the joint probability distribution function of the standard normal random vector ξ . These multivariate polynomials are given by $\Psi_{\beta} = \prod_{i=1}^M H_{\alpha_i}(\xi)$, where $H_{\alpha_i}(\cdot)$ is the α_i -th one-dimensional

Hermite polynomial and α_i are a sequence of M non-negative integers $\{\alpha_1, \dots, \alpha_M\}$. In practice, one should truncate the PCE representation by retaining only the multivariate polynomials of degree less than or equal to the PCE order p . For this reason, a classical truncation scheme based on the determination of the first order norm is generally adopted in the literature. This first order norm is defined as follows:

$\|\alpha\|_1 = \sum_{i=1}^M \alpha_i$. The classical truncation scheme suggests that the first order norm

should be less than or equal to the order p of the PCE. Using this method of truncation, the number P of the unknown PCE coefficients is given by $P = \frac{(M+p)!}{M!p!}$. Thus, the number P of the PCE coefficients increases dramatically

with the number M of the random variables and the order p of the PCE. To overcome such a problem, it was shown that the number of significant terms in a PCE is relatively small since the multidimensional polynomials Ψ_{β} corresponding to high-order interaction are associated with very small values for the coefficients a_{β} . Thus, a truncation strategy based on this observation was developed in which the multidimensional polynomials Ψ_{β} corresponding to high-order interaction were penalized. This was performed by considering the hyperbolic truncation scheme that considers the q -norm instead of the first order norm. The q -norm is given by

$\|\alpha\|_q = \left(\sum_{i=1}^M \alpha_i^q \right)^{1/q}$ where q is a coefficient ($0 < q < 1$). The hyperbolic truncation scheme

suggests that the q -norm should be less than or equal to the order p of the PCE. The proposed methodology leads to a SPCE that contains a small number of unknown coefficients which can be calculated from a reduced number of calls of the deterministic model. This is of particular interest in the present case of random fields which involve a significant number of random variables. This strategy will be used in this paper to build up a SPCE of the system response using an iterative procedure [Blatman and Sudret (2010)]. Once the unknown coefficients of the SPCE are determined, the PDF of the dynamic responses can be estimated using Monte Carlo technique.

NUMERICAL RESULTS

The aim of this section is to present the probabilistic results. It should be remembered here that the dynamic system responses involves the permanent displacement at the toe and the maximum amplification of the acceleration at the top of the slope. In this study, the effect of both the soil spatial variability and the time variability of Ground-Motion (GM) on the dynamic responses are considered. The soil shear modulus G is considered as an isotropic lognormal random field. The mean and the coefficient of variation of G are respectively $\mu_G = 112.5 \text{MPa}$ and $Cov_G = 40\%$. In order to simulate the stochastic synthetic time histories, the Kocaeli (Turkey 1999) earthquake is used as the target accelerogram (see Fig.1). The deterministic model is based on numerical simulations using the dynamic option of the finite difference code $\text{FLAC}^{3\text{D}}$. The slope geometry considered in the analysis is 10m in height and 45° in inclination angle (see Fig.2). It should be noted that the size of a given element in the mesh depends on both the autocorrelation distances of the soil properties and the wavelength λ associated with the highest frequency component f_{max} of the input signal. For the autocorrelation distances of the soil properties, Der Kiureghian and Ke (1988) have suggested that the length of the smallest element in a given direction (horizontal or vertical) should not exceed 0.5 times the autocorrelation distance in that same direction. As for the wavelength λ associated with the highest frequency component f_{max} of the input signal, Itasca (2000) has suggested that the smallest element should not exceed 1/10 to 1/8 this wavelength λ in order to avoid numerical distortion of the propagating waves. Respecting these two conditions, a size element of 2m was chosen to perform the dynamic analysis. For the boundary conditions, the bottom horizontal boundary was subjected to an earthquake acceleration signal and free field boundaries were applied to the right and left vertical boundaries. The numerical simulations are performed using an elastoplastic model based on the Mohr-Coulomb failure criterion. The corresponding model parameters are the shear modulus G which is modeled as a random field, the bulk modulus K , the cohesion c , the friction angel ϕ , the dilation angel ψ , and the soil unit weight which are considered as deterministic. The values of these deterministic parameters are as follows: $K=133 \text{MPa}$, $c=10 \text{kPa}$, $\phi=30^\circ$, $\psi=20^\circ$, and $\gamma=18 \text{kN/m}^3$.

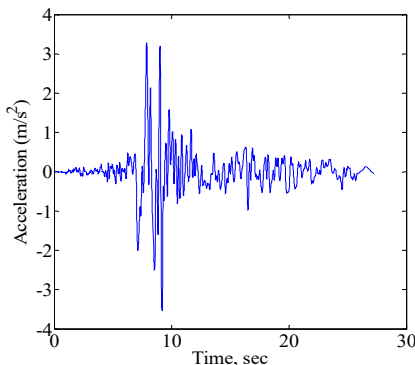


Figure 1. Kocaeli (Turkey 1999) accelerogram

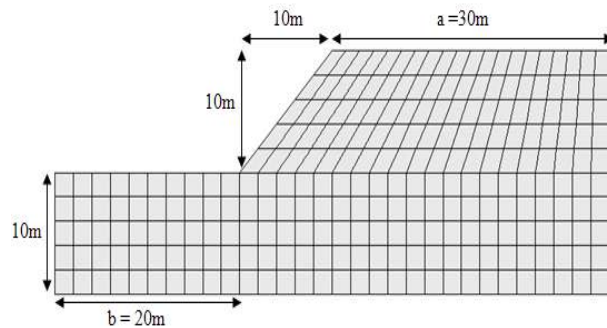


Figure 2. The slope geometry and $\text{FLAC}^{3\text{D}}$ mesh

In the following sections, one examines the effect of the soil spatial variability on both the amplification at the top and the permanent displacement at the toe of the slope using deterministic and stochastic GM accelerograms.

Effect of the soil spatial variability on the amplification at the top of the slope using deterministic and stochastic GM accelerograms

The effect of the soil spatial variability on the amplification at the top of the slope using deterministic and stochastic GM accelerograms is studied and presented in Figs 3, 4 and Table 1. Different values of the isotropic autocorrelation distance ($\theta=0.5, 1, 2, 3, 5$) were considered in the analyses. Notice that in the current study, the autocorrelation distance has been nondimensionalized by dividing it by the height of the slope. Figs 3 and 4 show that the PDF is less spread out when the isotropic autocorrelation distance θ decreases. The variability of the amplification at the top of the slope decreases with the increase in the soil heterogeneity (i.e. small values of θ). This can be explained by the fact that the fluctuations of the shear modulus are averaged to a mean value along the seismic wave's path propagation. This mean is close to the probabilistic mean value of the random field G . This leads to close values of the responses amplification and thus to a smaller variability in this response. Notice however that adding the randomness of the earthquake GM has a significant incidence on the variability of the amplification. Table 1 shows that for the range of the autocorrelation distances considered in this study, the coefficient of variation COV of the amplification is between 2.78% and 10.91% when deterministic GM accelerogram is used. This range of COV increases significantly when the randomness of the earthquake GM is introduced. In this case, the COV of the amplification have values between 4.23% and 31.78%. One can notice that for the largest autocorrelation distance $\theta=5$, the variability of the amplification in the case where stochastic GM accelerograms were used is 2.9 time larger than the one obtained with the deterministic GM accelerogram.

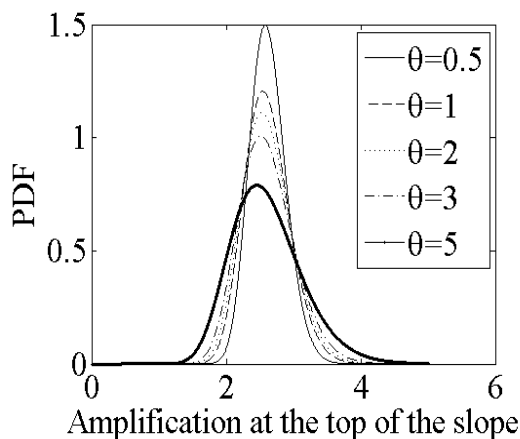


Figure 3. Amplification at the top of the slope with deterministic GM

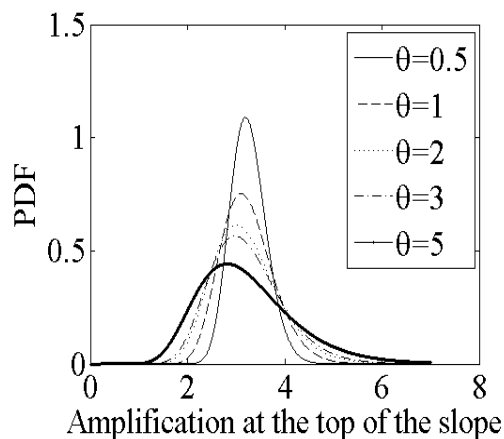


Figure 4. Amplification at the top of the slope with stochastic GM

Table 1 also shows that the autocorrelation distance θ has practically no effect on the mean value of the amplification. This mean value is shown to be larger than the corresponding deterministic value. This means that the probabilistic results are much more critical than the deterministic value with a difference of 5% in the case where deterministic GM accelerogram is used, and 29% in the case where stochastic GM accelerograms are used.

Table 1. Effect of the autocorrelation distance θ on the statistical moments (μ , σ) of the amplification

| | θ | Mean $\mu \times 10^{-2}$ (m) | Standard deviation σ | COV (%) | Deterministic amplification |
|---------------------|----------|----------------------------------|--------------------------------|---------|--------------------------------|
| Deterministic GM | 0.5 | 2.6 | 0.073 | 2.784 | 2.48 |
| | 1 | 2.6 | 0.114 | 4.364 | |
| | 2 | 2.6 | 0.135 | 5.176 | |
| | 3 | 2.6 | 0.166 | 6.362 | |
| | 5 | 2.6 | 0.285 | 10.915 | |
| | θ | Mean $\mu \times 10^{-2}$ (m) | Standard deviation σ | COV (%) | Deterministic amplification |
| Stochastic GM | 0.5 | 3.2 | 0.138 | 4.237 | 2.48 |
| | 1 | 3.2 | 0.301 | 9.301 | |
| | 2 | 3.2 | 0.472 | 14.610 | |
| | 3 | 3.2 | 0.567 | 17.565 | |
| | 5 | 3.2 | 1.030 | 31.780 | |

Effect of the soil spatial variability on the permanent displacement at the toe of the slope using deterministic and stochastic GM accelerograms

The effect of the soil spatial variability on the permanent displacement at the toe of the slope using deterministic and stochastic GM accelerograms is studied and presented in Figs. 5, 6 and Table 2. The same values of the isotropic autocorrelation distance θ used in the previous section are also used herein. Figs. 5 and 6 show that the PDFs are very close to each other and thus the shear modulus variability has a small influence on the permanent displacement. This is because the permanent displacement appears only when the plastic phase is reached which means that the effect of the shear modulus G on this response is relatively small. Table 2 confirms this observation because very small values of the COV of the permanent displacement are obtained when only the spatial variability of G is considered. On the other hand, one can see that introducing the randomness of the earthquake GM considerably affects the permanent displacement. High values of the COV are detected because of the important increase in the mean value of the permanent displacement due to the variability of the GM.

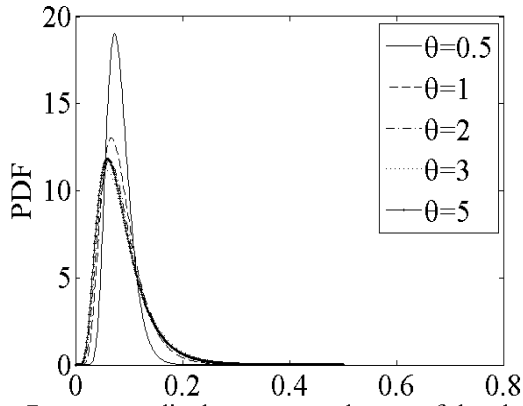


Figure 5. Permanent displacement at the toe of the slope with deterministic GM

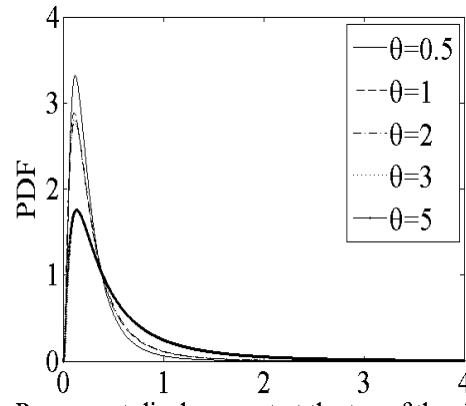


Figure 6. Permanent displacement at the toe of the slope with stochastic GM

Table 2 also shows that the mean value of the permanent displacement presents a maximum. This maximum was detected when $\theta=2$, i.e. when the isotropic autocorrelation distance is equal to the height of the soil domain. When θ decreases from 5 to 2, one can notice that the mean of the permanent displacement increases. This can be explained by the fact that increasing the soil heterogeneity introduces weak zones with small values of the shear modulus G , thus leading to larger values of the permanent displacement. The decrease in the permanent displacement for values of θ smaller than 2 may be explained by the fact that as the autocorrelation distance decreases, the propagating wave can face some stiff zones which reduce the permanent displacement. Finally, one can notice also that introducing the soil spatial variability and the randomness of GM lead to more critical results since all the mean values of the permanent displacement obtained in the probabilistic study are larger than the corresponding deterministic value.

Table 2. Effect of the autocorrelation distance θ on the statistical moments (μ , σ) of the permanent displacement

| | θ | Mean $\mu \times 10^{-2}$ (m) | Standard deviation σ | COV (%) | Deterministic permanent displacement |
|---------------------|----------|----------------------------------|--------------------------------|------------|---|
| Deterministic GM | 0.5 | 8.20 | 0.0005 | 0.610 | 0.0407 |
| | 1 | 8.62 | 0.0014 | 1.624 | |
| | 2 | 8.84 | 0.0020 | 2.262 | |
| | 3 | 8.75 | 0.0021 | 2.400 | |
| | 5 | 8.55 | 0.0025 | 2.924 | |
| | θ | Mean $\mu \times 10^{-2}$ (m) | Standard deviation σ | COV (%) | Deterministic permanent displacement |
| Stochastic GM | 0.5 | 26.20 | 0.0596 | 22.75 | 0.0407 |
| | 1 | 26.46 | 0.1248 | 47.16 | |
| | 2 | 27.40 | 0.1267 | 46.24 | |
| | 3 | 27.17 | 0.1359 | 50.02 | |
| | 5 | 25.57 | 0.2793 | 109.23 | |

CONCLUSIONS

The effect of both the soil spatial variability and the Ground-Motion (GM) time variability on the dynamic responses is studied. The soil shear modulus G is considered as an isotropic non-Gaussian random field. The simulation of variable acceleration time histories based on a real target accelerogram is done using a fully nonstationary stochastic model. The deterministic model was based on numerical simulations using the dynamic option of the finite difference code FLAC^{3D}. The methodology adopted in this paper makes use of a non-intrusive approach to build up a sparse polynomial chaos expansion (SPCE) for the dynamic system responses. The main conclusions can be summarized as follows: (i) the decrease in the autocorrelation distance of G (i.e. the soil heterogeneity) leads to a small variability of the dynamic responses; the amplification being more affected; (ii) adding the randomness of the earthquake GM has a significant incidence on the variability of the dynamic responses; (iii) the isotropic autocorrelation distance affects the probabilistic mean values of plastic responses (eg. the permanent displacement); its effect being negligible on elastic responses (eg. the amplification).

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